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Daily disaggregation of simulated monthly flows using different rainfall datasets in southern Africa

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ABSTRACT

Study region: Selected countries in southern Africa.

Study focus: The study uses a combination of a monthly rainfall-runoff model and a daily rainfall based disaggregation method to simulate daily flows. The two models were forced with different rainfall data (local and global) and the results examined to determine the major reasons for modelling success or failure.

New hydrological insights for the region: There are substantial regional differences in the success of the monthly hydrological model, which inevitably affects the success of the daily disaggregation results. There are also regional differences in the success of using global rainfall data sets (Climatic Research Unit (CRU) datasets for monthly, National Oceanic and Atmospheric Administration African Rainfall Climatology, version 2 (ARC2) satellite data for daily). The overall conclusion is that the disaggregation method presents a parsimonious approach to generating daily flow simulations from existing monthly simulations and that these daily flows are likely to be useful for some purposes (e.g. water quality modelling), but less so for others (e.g. peak flow analysis).

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1. Introduction

There are many parts of the developing world where establishing hydrological and water resources estimation models is difficult due to the lack of observed stream flow data for calibration and validation purposes, as well as deficiencies in the available climate input data to force the models. The former can be partially overcome through parameter regionalisation approaches that also include uncertainty assessments (Yadav et al., 2007; Kapangaziwiri et al., 2012). Even when observed stream flow data are available, they often include upstream anthropogenic impacts which are not always adequately quantified (Hughes and Mantel, 2010), or are not included as part of the modelling scheme. The availability of climate forcing data is problematic as a consequence of a lack of observation stations, a situation that is getting steadily worse (WWAP, 2009), combined with difficulties in accessing climate databases from some national authorities. Some data custodians are reluctant or lack the capacity to respond to data requests, and in some cases only summary information is available rather than complete time series of raw data. In other situations, quite substantial charges are levied before the data are released, even if the request is for research purposes. Practical hydrological modellers are therefore faced with decisions related to the choice of model, what data they are going to use to force the model and how they are going to validate or justify the results. All of these issues are strongly interrelated and typically not easy to resolve in many data scarce areas of southern Africa.

From a practical perspective (rather than for research purposes), the selection of a model would typically be based on user experience and the extent to which a model has already been applied successfully in the region of interest. The Pitman monthly rainfall-runoff model is therefore often the model of choice in the southern Africa region (Hughes, 2013) and it is often coupled with water resources system yield models (Basson et al., 1994; Mallory et al., 2008) to cater for many different anthropogenic impacts and to simulate different development scenarios. However, there are also situations where a monthly time-step might be considered too coarse, and either daily modelling or some form of daily disaggregation would be required.

There are many parts of southern Africa where both observed rainfall and stream flow data are limited in terms of spatial coverage and lengths of record. There is little that can be done about the stream flow data, and it is inevitable that many of our hydrological simulations will be impossible to validate and are therefore highly uncertain (Kapangaziwiri et al., 2012). Arguably, one of the only options is to use regionalised catchment response information to constrain the uncertainty as far as possible (Yadav et al., 2007; Tumbo and Hughes, 2015). For rainfall data, the alternative to a lack of local ground-based data is to make use of freely available global datasets that have been compiled through spatial interpolation from existing data, or that use remotely sensed data, such as satellite rainfall data (Voisin et al., 2008; Pombo et al., 2014; Prakash et al., 2014). All of the available data products have different temporal and spatial resolutions and therefore, not all of them are necessarily appropriate for a specific study. They are also potentially biased in relation to local ground-based rainfall data, and the bias is expected to vary depending on the amount of local rainfall data incorporated into the interpolated or merged products. The effects of topography and related orographic rainfall producing mechanisms are expected to introduce further bias in satellite products (Hughes, 2006; Xie and Arkin, 1995).

This paper reports on the results of a study that involved the simulation of both monthly (using the Pitman model) and daily (disaggregating the Pitman monthly simulations) stream flows using different rainfall data products for a group of catchments covering different climate and topographical characteristics in southern Africa and with different degrees of data quality and scarcity. The objective of the study was partly to further test a daily disaggregation approach (Slaughter et al., 2015) and partly to compare the results of applying both models with different rainfall data products. More specifically, the study was designed to try and identify any key limitations of the models coupled with typically available rainfall data for different practical water resources assessment purposes.

Table 1
Catchments used in the study.

Catchment name	Area (km^2)	No. of rain gauges	Water balance ($mm\,y^{-1}$)	Lat Long.	Brief description of climate and location
C2H066	1101	3	517:15 2.9%	−27.20 26.01	Semi-arid, flat to undulating tributaries of the Vaal River, South Africa.
C7H003	914	3	553:19 3.5%	−27.48 27.44	
C8H005	696	3	650:152 23.4%	−28.55 28.84	Semi-arid area draining the north slopes of the Drakensberg Mountains, Free State, South Africa.
K3H003	145	3	777:180 23.1%	−33.94 22.32	Sub-humid Southern Cape of South African coastal areas with steep topography affected by orographic precipitation.
K4H003	72	3	777:130 16.7%	−33.88 22.69	
K7H001	57	3	1000:466 46.6%	−33.92 23.66	
T4H001	715	3	868:231 26.6%	−30.66 29.71	Sub-humid to humid with undulating to steep topography of the Eastern Cape, South Africa.
W3H014	48	3	927:77 8.3%	−28.34 32.33	Humid coastal area of NE KwaZulu-Natal, South Africa with flat topography.
BOT_Tati	570	6	460:53 11.4%	−21.00 27.50	Arid areas in the headwaters of the Shashe River, Botswana. Gently, undulating topography.
BOT_Ntse	800	6	460:37 8.1%	−21.00 27.30	
SWZ_WMbl	223	3	810:104 12.9%	−26.37 31.42	Headwaters of the Mbululzi River, Swaziland. Sub-humid and close to a N-S aligned steep escarpment.
SWZ_BMbl	722	4	1231:324 26.3%	−26.22 31.30	
TZ_1KA8A	783	0	1408:585 41.5%	−9.03 34.12	Sub-humid, steep headwaters of the Great Ruaha River, Tanzania.
ZAM_4005	433	2	1236:112 9.0%	−12.10 26.80	Sub-humid, undulating headwaters of the Kafue River in Zambia.
ZAM_7005	444	3	1199:286 23.8%	−9.25 31.00	Sub-humid, undulating area of NE Zambia near Lake Tanganyika.
ZIM_B15	274	5	641:97 15.1%	−20.60 28.81	Semi-arid, relatively steep topography areas of SW Zimbabwe.
ZIM_B29	362	5	642:78 12.1%	−20.60 28.80	
ZIM_D6	1170	5	890:255 28.7%	−16.90 31.75	Semi-arid to sub-humid, relatively steep topography areas of NE Zimbabwe.
ZIM_D46	202	3	838:168 20.0%	−17.20 32.09	

Notes: The three values given in the 'water balance' column are (in order) mean annual rainfall: mean annual runoff (both in $mm\,y^{-1}$) and runoff ratio as a percentage. No local rain gauges were available for TZ_1KA8A and the rainfall data used were based on regional interpolation (Stisen and Tumbo, 2015).

2. Study areas, models and data

2.1. Catchment selection

The catchments included in the analyses (Table 1) were selected partly to be representative of typical conditions within the sub-continent, partly on the basis of the availability of both daily rainfall and daily flow data and partly because of the existence of some prior modelling experience. In selecting the catchments it was recognised that not all of them would have very high quality data available. However, this is a limitation that is faced by all practical applications of hydrological models within the sub-continent and therefore, arguably, should be included as an important issue in any evaluation of the usefulness of hydrological models. All of the catchments are small to moderate sized (>20 km^2 and less than 2000 km^2) and have either relatively minor anthropogenic impacts on the flow regimes, or well-defined impacts (such as afforestation) that can be included as part of the model setup. The modelling experience for the South African catchments is largely derived from many applications of the Pitman model (Hughes, 2013) in the country, including the national water resources assessment of Midgley et al. (1994) and follow-up studies. The experience for the other countries is derived from the results of the UNESCO southern African FRIEND (Flow Regimes from International Experimental and Network Data) project (Hughes, 1997).

2.2. Models

Two models are used within this study. The first is the monthly time-step, Pitman rainfall-runoff model (Pitman, 1973) that has been applied in the region many times (Hughes, 2013) for both research and practical purposes. The Pitman model is a conceptual type model that includes explicit components to represent all of the key, catchment-scale, hydrological processes relevant to the southern Africa region (interception, surface runoff, interflow, groundwater recharge and discharge to stream flow, evapotranspiration, etc.). The model is semi-distributed and requires inputs of monthly precipitation and seasonal distributions of mean monthly potential evaporation for each sub-basin. There are a total of 14 parameters that are typically calibrated. The second model is a disaggregation model that uses daily rainfall data to disaggregate simulated monthly flows to daily flows (Slaughter et al., 2015). This model was developed as part of an on-going project that is designed to link water quality modelling to existing monthly time-step water quantity models of both natural hydrology (rainfall-runoff models) and water use (water resources system yield models). The rationale for the development of this model was that, while water quantity and water use dynamics can be satisfactorily simulated at a monthly time scale (Mallory et al., 2008; Hughes, 2013), water quality cannot. Consequently, most established water quality models are run at a daily time-step or less, for example SWAT (Arnold et al., 1998), QUAL2K (Pelletier et al., 2006) and CE-QAUL-W2 (Cole and Buchak, 1995). While a daily hydrological model could be used to force a water quality model, there are distinct practical advantages to linking the quality model to existing quantity estimates generated by a combination of the Pitman model and systems yield models (Basson et al., 1994; Mallory et al., 2008). There are many existing monthly model set-ups within several countries of southern Africa that have been accepted, and are used, by the broad community of water resources managers. The daily disaggregation approach is designed to add value to these. A daily disaggregation approach is also potentially valuable for linking monthly rainfall-runoff model outputs to a number of other water resources management tools that operate on a daily time-step, including hydraulic modelling of floodplain inundation (Schumann et al., 2013), short-term (within month) irrigation abstraction management (George et al., 2000), environmental flows (Overton et al., 2014) and flood frequency analysis. Arguably, monthly rainfall-runoff models are easier to establish than daily models in regions such as southern Africa, particularly given the difficulties of obtaining long time series of daily rainfall data and the long history of experience with the Pitman model (Hughes, 2013). The availability of an additional procedure that can reliably disaggregate the simulated monthly flows to daily estimates therefore has the potential to contribute to a number of water resources management issues. However, this will only be possible if appropriate estimates of daily rainfall are available that can be used to force the disaggregation approach.

The full details of the Pitman model are not provided here and can be accessed from several of the publications referred to in Hughes (2013). The daily rainfall disaggregation model is less well documented in the literature (Slaughter et al., 2015) and is therefore summarised in Fig. 1. Step 1 simply refers to the generation of a flow duration curve (FDC) from simulated monthly flow data, while Step 2 refers to the quantification of the parameters of an equation used to scale the monthly flow quantiles to create an equivalent and representative daily FDC. Steps 3 and 4 refer to the use of daily rainfall data to generate a continuous time series of an antecedent precipitation index (API) and the associated exceedance frequency distribution (Smakhtin and Masse, 2000). The implied assumption of this approach is that it should be flexible enough (through different values of the K and P_{Thresh} parameters) to account for the runoff response dynamics of catchments with different sizes and physical

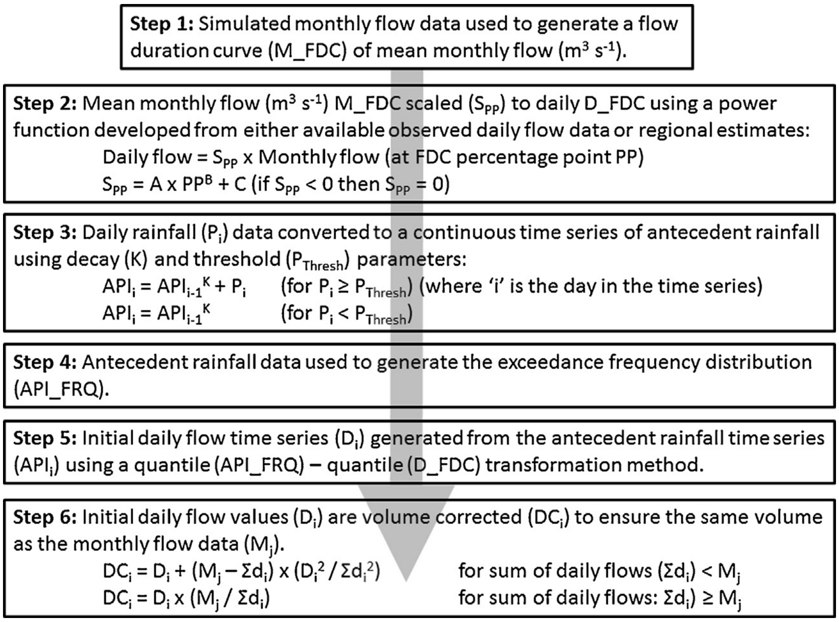

Fig. 1. Summary of the 6 steps involved in the daily disaggregation model.

characteristics. A quantile–quantile transformation approach is used to translate the API time series into initial daily flows (Step 5), which are then volume corrected to ensure the same monthly volumes as the monthly flow data (Step 6). Slaughter et al. (2015) includes further details and a diagrammatic representation of the approach.

2.3. Data

The local station South African data were obtained from the national agencies that collect the data; the South African Weather Service (SAWS) for rainfall data and the Department of Water and Sanitation for stream flow data. Lynch (2004) infilled the missing data periods in some of the raw SAWS data and these data sets are used here. The data (rainfall and stream flow) for the other catchments were obtained from the other national hydrometeorological agencies during the Southern Africa FRIEND project (Hughes, 1997) and no recent attempts were made to update and extend these data sets. Both the daily and monthly local station data were compiled using several rain gauges (Table 1, column 3) and an inverse distance squared weighting (IDSW) method to combine the observed data into a catchment average time series covering the longest possible period. While alternative spatial interpolation methods are available (Thiessen polygons, kriging, etc.), local experience suggests that there are few differences in the results when there are a limited number of available gauges. The IDSW method is also very straightforward to apply in GIS software. Individual gauges within the same catchment have different length records and different amounts of missing data. The extent to which different periods within the final time series of local catchment average rainfalls can be considered representative therefore largely depends on the location of the rainfall stations with available data during those periods. Double mass curve analyses between the local station data and the long-term global monthly data (see below) were used for a simple assessment of the temporal consistency of the catchment average rainfall estimates. These revealed that the first 20 years (1900–1919) of the local estimates for T4H001 and W3H014 could not be considered representative and were not used in the analysis. Further inspection of the rainfall data did not reveal any trends that might be associated with climate change and therefore the data are considered to be essentially stationary.

Table 2
Comparisons between local and global rainfall data for monthly and daily time scales.

Catchment	Local station data		Monthly rainfall:local vs CRU		Daily rainfall:local vs ARC2		
	Period of record	Mean monthly rainfall (mm)	R^2	Bias (%)	R^2	Bias (%)	Method
C2H066	1900–2009	43.0	0.758	4.4	0.939:0.150	0.4:−17.4	FRQ:T/S
C7H003	1900–2009	46.1	0.728	8.2	0.977:0.099	−9.7:−8.0	FRQ:T/S
C8H005	1905–2009	54.2	0.806	43.9	0.988:0.239	14.8:−4.3	FRQ:T/S
K3H003	1900–2009	64.7	0.524	−37.8	0.915:0.347	−31.8:−9.7	FRQ:T/S
K4H003	1900–2009	64.7	0.608	−0.8	0.948:0.241	−31.7:15.8	FRQ:T/S
K7H001	1900–2005	83.4	0.778	−20.8	0.789:0.301	−67.8:−43.3	FRQ:T/S
T4H001	1920–2009	76.8	0.743	−2.1	0.980:0.142	−8.7:−8.6	FRQ:T/S
W3H014	1900–2009	80.3	0.552	15.3	0.978:0.680	0.6:−5.6	FRQ
BOT_Tati	1922–1992	38.3	0.914	−11.1	0.985	6.9	FRQ
BOT_Ntse	1922–1992	38.3	0.938	5.1	0.985	5.1	FRQ
SWZ_WMbl	1905–1989	67.5	0.843	43.1	0.945	−23.8	FRQ
SWZ_BMbl	1905–1992	102.6	0.884	−6.2	0.793	−50.0	FRQ
TZ_1KA8A	1960–2009	117.3	0.810	−30.8			N/A
ZAM_4005	1951–1988	103.0	0.854	4.9			N/A
ZAM_7005	1919–1991	99.9	0.939	−0.6			N/A
ZIM_B15	1952–1983	53.4	0.907	−24.5	0.936	−24.4	FRQ
ZIM_B29	1952–1983	53.5	0.900	−24.7	0.856	−21.4	FRQ
ZIM_D6	1949–1983	74.2	0.888	−0.2	0.979	−15.0	FRQ
ZIM_D46	1968–1983	69.8	0.914	23.5	0.962	−13.0	FRQ

Notes: The periods of record extend from October of the first year to September of the last year.
The 'method' column refers to the approach used for daily data comparison, where T/S uses a daily time series comparison and FRQ uses a comparison of the percentage points of the daily rainfall exceedance frequency curve in the absence of overlaps between the local and satellite data.

The long-term global monthly rainfall data (CRU TS v.3.22: Harris et al., 2014) that have been used in the study were downloaded (during June 2014) from the website of the Climate Research Unit (CRU) at East Anglia University, UK (http://www.cru.uea.ac.uk/cru/data/hrg/cru_ts_3.22/). These are monthly rainfall depths covering the period of January 1901 to December 2012 for $0.5^\circ \times 0.5^\circ$ grids covering the entire globe and are based on the interpolation of local rainfall station data. In this study the data for October 1901 to September 2012 were used. The CRU data have been used successfully in other regional precipitation studies worldwide (e.g. Lovino et al., 2014; Los, 2015). The satellite data used in the study are the NOAA (National Oceanic and Atmospheric Administration) CPC (Climate Prediction Center) ARC2 data downloaded during July 2014 (ftp://ftp.cpc.ncep.noaa.gov/fews/fewsdata/africa/arc2/bin) and represent daily rainfall totals for a $0.1^\circ \times 0.1^\circ$ grid covering 50°N–50°S and 40°W–40°E (Novella and Thiaw, 2013). While the data extend from 1983 to the present day, only data for October 2000 to September 2012 were used in this study as there are many missing values in the earlier parts of the time series. The data are based on a combination of key local station data and microwave observations of cloud top temperature from geostationary satellites. The record periods of all data sets (rainfall and stream flow) are summarised in Fig. 2.

3. Methods

3.1. Rainfall data comparisons

The first part of the analysis involved simple statistical comparisons of the local and global rainfall datasets. For the monthly data, this involved calculations of the coefficient of determination (R^2) values and the percentage bias (%Bias in Eq. (1)) of the mean monthly CRU rainfall (MMP_{CRU}) relative to the mean monthly local rainfall (MMP_{local}) for the total period of overlap (Table 2, column 2).

$$\%\text{Bias} = (\text{MMP}_{\text{CRU}} - \text{MMP}_{\text{local}}) * 100/\text{MMP}_{\text{local}} \tag{1}$$

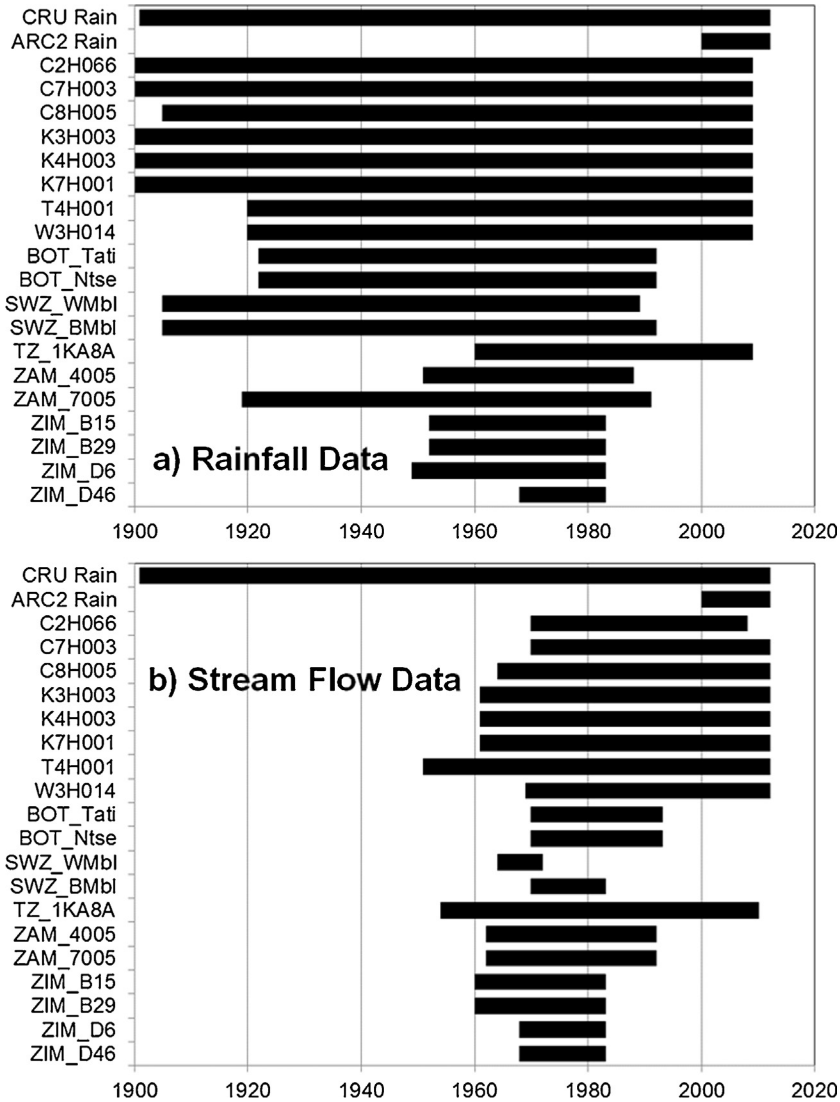

Fig. 2. Record lengths of the rainfall data (a) and the observed stream flow data (b) used in the study (the CRU and ARC2 rainfall periods have been included in (b) to facilitate comparisons).

As the satellite rainfall data have a shorter, and later, period of record, a similar comparison using daily data was only possible for the South Africa catchments (Table 2, column 8 = T/S) where local rainfall data after October 2000 were available. For some of the other catchments, earlier periods of local daily rainfall data were available and the comparison statistics were based on a set of fixed quantiles of the frequency of exceedance distributions (Table 2, column 8 = FRQ). The fixed quantiles were identified at percentage points 0.05, 0.1, 0.5, 1, 1.5, . . ., 9.5, 10, 11, etc. up to the exceedance frequency at which the rainfall for both data series is above 1 mm. This approach was used as the local and satellite data have different record lengths. In some cases (Table 2, column 7 = 0) no daily rainfall data were available. It should be noted that the ARC2 data are based on a day that starts at 00h00 (GMT) while the local data are typically based on a day starting at 08h00 local time. A high level of correlation between individual daily values is not therefore expected, while the quantile assessment should reveal any bias in the frequency of different depths of rainfall.

3.2. Hydrological modelling at the monthly time scale (Pitman model)

The uncertainty version of the Pitman model (Hughes et al., 2010; Hughes, 2013) was established for each of the catchments using existing evaporation demand data (from various previous studies) and both the local and bias corrected CRU monthly rainfall data. Only a simple bias correction (all monthly CRU rainfalls scaled to remove the bias in the mean rainfall given in Table 2, column 7) was applied in this study and no attempts were made to apply different correction factors to different quantiles of the exceedance frequency distribution. This simple approach was adopted because we wish to assess the usefulness of the CRU data in situations where alternative data are not available. In such situations regional estimates of long-term mean rainfall are likely to be available to perform the simple bias correction, but no additional data would be expected to be available to perform a quantile bias correction.

The uncertainty version of the model is based on setting likely parameter ranges and generating 10,000 simulation ensembles using independent Monte Carlo sampling from uniform distributions defined by minimum and maximum parameter values. All of the parameters considered to be uncertain are independently sampled, while some of the parameters that have minor impacts on the total water balance dynamics are not treated as uncertain. The initial parameter ranges were established through a limited number of manual calibrations of the model using the local station rainfall data and based on many years of experience of applying the model in the southern African region (Hughes, 2013). The uncertainty model outputs were analysed to determine the parameter sets that generate the best overall results based on comparisons with observed stream flow data using a set of statistics including Nash–Sutcliffe efficiency values (Nash and Sutcliffe, 1970) and mean monthly bias values (Eq. (1)) using untransformed (NSE and %Bias) and log transformed (NSE{ln} and %Bias{ln}) data. The results can also be used to explore the potential benefits of using different input uncertainty ranges for some of the parameters (i.e. a relatively simple sensitivity analysis). It is therefore possible to compare the model performance and the change in the values of behavioural parameter sets (those that give the best values of the performance statistics) when the model is forced with the bias corrected CRU data compared to when local rainfall data are used.

3.3. Disaggregation to daily flows

The first steps in the application of the disaggregation model were to calibrate the FDC scaling parameters (Fig. 1, Step 2) and the rainfall API parameters (Fig. 1, Step 3). These calibrations were performed with observed daily flow volumes to avoid problems related to using poorly simulated monthly flow volumes (Slaughter et al., 2015). In situations where no observed daily flow data are available, this approach is clearly not possible and regionalised parameter values would have to be used.

The monthly flow ensemble simulation results with the ‘best’ performance (using local and CRU data) were then used within the disaggregation model together with local (where possible) and satellite daily rainfall data. Three analyses were performed. The first used the monthly flows simulated with the local rainfall data and disaggregated with local daily rainfall data (Local–Local). The second used the monthly flows simulated with CRU rainfall data and disaggregated with local daily rainfall data (CRU–Local), while the third used the same CRU simulated flows but disaggregated with the ARC2 daily satellite data (CRU–ARC2). The third analysis was only possible for those sites where the observed flow data overlap with the ARC2 data period. Any systematic bias in the satellite rainfall data should not affect the results of the disaggregation as only the rainfall API frequency characteristics are used (Slaughter et al., 2015) and therefore, it was not considered necessary to bias correct the satellite data. The assessments of the simulated daily flows are based on direct comparisons with the time series of observed daily flow data, as well on comparisons between simulated and observed FDC quantiles (using the same data periods). A separate version of the disaggregation model was developed to allow multiple monthly simulated ensembles to be used and to examine the extent to which the range of simulated daily flows bracket the observed daily flows.

4. Results analysis

4.1. Monthly rainfall data comparisons

Not surprisingly, some of the catchments with the worst statistics of comparison between local station and CRU data (Table 2, columns 4 and 5) are those where the large scale of the CRU grids is likely to generate poor estimates of catchment rainfall. This includes the three Southern Cape catchments (K3H003, K4H003 and K7H001) which drain a coastal mountain range where there are large topographically related spatial rainfall variations that are within a CRU grid. The same applies to the Swaziland (SWZ_WMbl and SWZ_BMbl) and the Tanzanian (TZ_1KA8A) sites that are located on the edge of escarpments with steep rainfall gradients within a single CRU grid. The high positive bias for C8H005 may be related to the location of the catchment close to the Drakensberg Mountains where there are few rain gauges. The relatively poor R^2 value for W3H014 is more difficult to explain. It is important to note that relatively poor comparison statistics does not necessarily mean that the CRU data are less representative than the local data, and may be a reflection of poorly located local rainfall stations or stations with lower accuracy data.

4.2. Daily rainfall data comparisons

As might have been anticipated, the R^2 values for the daily time series comparisons between the local and ARC2 data are almost always very low (Table 2). This is partly related to different definitions of a ‘day’ between the two data collection systems. The R^2 values based on exceedance frequency distributions (FRQ) are, however, generally very good. This is a very positive conclusion given the way in which the satellite data are used within the disaggregation process (Fig. 1). Many of the FRQ bias values are in line with expectations, in that they are generally high and negative in mountainous areas (K3H003, K4H003, K7H001, SWZ_WMbl and SWZ_BMbl) where satellite data are not expected to accurately quantify the orographic rainfall gradients (Hughes, 2006; Thiemig et al., 2012). It is, however, interesting to note that there is one situation (K4H003) where the sign of the bias is different for the FRQ and T/S analysis.

4.3. Monthly stream flow comparisons

The ‘best’ ensemble for each of the model runs was selected using the following standard approach and the results are provided in Table 3 for the runs forced with both local and CRU rainfall data:

- Step 1: Select those ensembles for which the absolute values of the %Bias and %Bias{ln} were less than 5.0.
- Step 2: Within the low bias ensembles select the one that has the highest combination of NSE and NSE{ln} objective functions.
- Step 3: Compare the observed and simulated flow duration curve shapes and repeat Step 2 with less stringent requirements for the other statistics if these do not compare very well.

There were situations where some of the selection criteria had to be relaxed in order to meet the other criteria and Table 3 includes results with %Bias or %Bias{ln} values in excess of 5.0.

For the model runs forced with local rainfall data, the results in Table 3 suggest that there are several catchments where the simulations can be considered good (NSE values better than 0.75), some with adequate simulations (0.5 < NSE < 0.75), some poor (0.0 < NSE < 0.5) and three bad (NSE < 0.0). In all the bad cases, the results are associated with a lack of coincidence in the timing of high (or low)

Table 3
Monthly Pitman model results after uncertainty runs and selection of the 'best' ensemble.

Catchment name	Rainfall data	NSE	NSE{ln}	%Bias	%Bias{ln}	Comments
C2H066	Local	0.468	0.076	−4.5	0.1	Peak rainfalls not represented in
	CRU	0.456	0.152	−25.1	−35.1	CRU data.
C7H003	Local	−0.099	0.139	1.5	−73.0	CRU rainfall timing appears better
	CRU	0.244	0.204	−18.7	−66.4	than local, but peaks are missed.
C8H005	Local	0.462	0.599	−4.0	4.8	Little difference in two simulations.
	CRU	0.476	0.604	4.9	4.9	
K3H003	Local	0.395	0.449	−3.5	0.8	Little difference in two simulations.
	CRU	0.368	0.336	−4.9	4.8	
K4H003	Local	0.617	0.455	−5.0	−4.2	High peak flows are missed by CRU
	CRU	0.292	0.299	−4.3	−4.9	simulations.
K7H001	Local	0.702	0.596	−2.3	4.4	High peak flows are missed by CRU
	CRU	0.453	0.405	−1.3	4.9	simulations.
T4H001	Local	0.745	0.824	−0.2	2.0	CRU timing is generally worse than
	CRU	0.363	0.611	−4.6	2.1	for local rain data.
W3H014	Local	−0.393	0.237	−1.3	−4.1	Model performs badly, but CRU
	CRU	0.443	0.387	−27.2	−10.7	gives better timing.
BOT_Tati	Local	0.823	0.133	5.0	3.7	Not large differences between the
	CRU	0.671	0.002	3.9	−4.6	Botswana simulations. Ln based
BOT_Ntse	Local	0.776	0.108	4.6	−23.3	statistics are not good indicators of
	CRU	0.714	−0.208	−1.8	−35.3	performance.
SWZ_WMbl	Local	0.796	0.716	0.2	0.3	CRU generally poorer performance.
	CRU	0.605	0.669	−4.1	3.8	
SWZ_BMbl	Local	0.797	0.854	−1.7	0.4	CRU over-simulates volume
	CRU	0.526	0.788	17.1	5.4	through most ensembles.
TZ_1KA8A	Local	0.745	0.613	−3.8	1.3	Similar simulations.
	CRU	0.646	0.635	1.1	4.8	
ZAM_4005	Local	−0.297	0.033	−3.4	20.1	Model performs badly, but CRU
	CRU	0.499	0.314	−10.6	142.4	gives better timing.
ZAM_7005	Local	0.709	0.722	2.1	2.9	No real differences between model
	CRU	0.748	0.771	1.7	2.1	performances.
ZIM_B15	Local	0.703	0.579	−3.7	−12.3	These are short observed flow
	CRU	0.724	0.620	−4.7	−3.7	records, but both rainfall data sets
ZIM_B29	Local	0.677	0.498	−3.4	−1.5	give similar results (CRU slightly
	CRU	0.750	0.509	−4.9	1.2	better overall).
ZIM_D6	Local	0.817	0.792	−3.7	4.4	CRU simulations poorer for higher
	CRU	0.662	0.806	−3.9	3.8	flows.
ZIM_D46	Local	0.898	0.863	−1.2	1.0	Generally similar results for the
	CRU	0.809	0.804	0.6	−4.1	two simulations.

rainfall amounts and high (or low) observed stream flow responses. No amount of parameter re-calibration can resolve this problem. When the model is forced with the bias corrected CRU rainfall data, it is surprising that all of the bad simulations are changed to the poor category and this is partly due to the fact that the higher CRU rainfall months are sometimes more coincident with the higher observed stream flow months. There are several catchments where ensembles with high negative %Bias values were accepted in order to obtain better NSE values. There were also catchments where poor simulations were associated with under-estimation of peak monthly flows when the CRU data were used (C2H066, K4H003, K7H001), which may be the result of spatial averaging of high rainfall months within the coarse scale CRU rainfall data. This problem cannot typically be resolved by changes in model parameters because changes that improve the high flow simulations have an adverse effect on other parts of the time series.

Although the details of the parameter sets that generated the selected ensembles are not provided here, it was noted that there were few differences between the model runs forced with CRU data compared to those forced with local data. Part of this result is almost certainly related to the fact that the CRU data were bias corrected to match the mean monthly rainfall of the local data. Had the uncorrected CRU data been used, it is inevitable that very different parameter sets would have been required where the CRU rainfall bias was large (Table 2, column 5).

Table 4
Calibrated disaggregation parameters. The API parameters are based on using observed flow volumes disaggregated with either local daily rainfall or ARC2 daily rainfall.

Catchment name	FDC scaling parameters			API parameters			
				Local daily rainfall		ARC2 daily rainfall	
	A	B	C	K	P_{Thresh} (mm)	K	P_{Thresh} (mm)
C2H066	0.4	−0.45	−0.10	0.995	10.0	0.995	3.0
C7H003	0.2	−0.70	0.30	0.995	1.0	0.990	1.0
C8H005	1.5	−0.60	0.50	0.980	13.0	0.990	3.0
K3H003	0.8	−0.50	0.40	0.960	8.0	0.960	1.0
K4H003	0.6	−0.70	0.70	0.980	15.0	0.960	18.0
K7H001	1.1	−0.50	0.40	0.990	1.0	0.980	1.0
T4H001	0.6	−0.50	0.80	0.995	5.0	0.995	1.0
W3H014	0.7	−0.60	0.50	0.980	15.0	0.970	5.0
BOT_Tati	2.0	−0.60	−0.35	0.970	1.0	N/A	N/A
BOT_Ntse	2.0	−0.60	−0.30	0.970	1.0	N/A	N/A
SWZ_WMbl	0.7	−0.90	0.80	0.990	3.0	N/A	N/A
SWZ_BMbl	0.6	−0.50	0.80	0.990	10.0	N/A	N/A
TZ_1KA8A	0.8	−0.50	0.80	N/A	N/A	0.995	20.0
ZAM_4005	0.6	−0.30	0.30	N/A	N/A	N/A	N/A
ZAM_7005	0.2	−0.50	0.95	N/A	N/A	N/A	N/A
ZIM_B15	1.1	−0.50	0.30	0.990	3.0	N/A	N/A
ZIM_B29	1.1	−0.40	0.30	0.995	8.0	N/A	N/A
ZIM_D6	0.7	−0.50	0.70	0.995	7.0	N/A	N/A
ZIM_D46	0.5	−0.50	0.70	0.990	8.0	N/A	N/A

Note: N/A means that either observed daily rainfall data or flow data are not available to perform the calibration.

4.4. Calibrating the disaggregation model

There are two sets of parameters that need to be quantified for the daily disaggregation model, the A, B and C parameters of the monthly to daily FDC scaling equation (Step 2 in Fig. 1), and the K and P_{Thresh} parameters of the procedure to convert daily rainfall into a continuous time series of API values (Step 3 in Fig. 1). Where some observed stream flow data are available (as in this study) scaling parameters can be determined by comparing the daily and mean monthly (both in $m^3 s^{-1}$) FDCs and fitting the parameters either manually or using an automatic search process together with appropriate fitting statistics. In the absence of observed flow data, regionally appropriate values will have to be determined from other stations where observed data are available.

Quantifying the K and P_{Thresh} parameters is a much more difficult process, even when observed daily stream flow data are available, as the results are dependent upon both the monthly stream flow volumes used as well as the representativeness of the daily rainfall data. If observed flow data are available it is better to use patched observed monthly flow volumes (i.e. the 'near perfect' volumes referred to in Slaughter et al., 2015) to avoid problems associated with poorly simulated monthly flows. Even then, this study revealed that commonly used comparison statistics (NSE) are frequently of little value if the temporal variations in daily rainfall and observed stream flow do not match. This is particularly true in semi-arid catchments which have substantial spatial rainfall variability which is not adequately represented by the limited observed rainfall data. It was therefore decided that calibrating K and P_{Thresh} should also be based on comparisons between the observed and simulated FDCs, supported by visual comparisons of the two time series to ensure that the general patterns of response are adequately simulated. The calibrated disaggregation parameters are presented in Table 4 and the results are summarised in Figs. 3 and 4. These include the API calibrations using both local (Fig. 3) and ARC2 (Fig. 4) daily rainfall.

It is very difficult to determine what represents realistically acceptable comparison statistics for daily flow simulations in southern African catchments given the accuracy and other limitations of both the available flow and rainfall data. The only available guidelines covering a number of

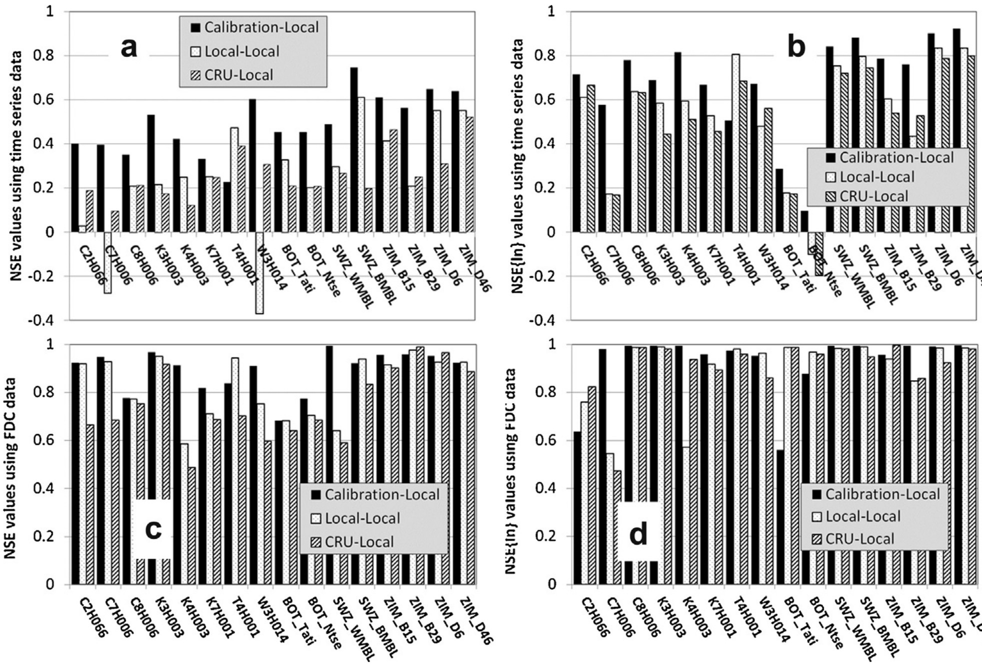

Fig. 3. NSE and NSE{ln} objective functions for the simulated daily flows time series (a and b) and flow duration curves (c and d) compared with observed data. 'Calibration' refers to the use of observed flow volumes, 'Local–Local' refers to using local rainfall data in both the rainfall-runoff and disaggregation models, while 'CRU–Local' refers to using CRU data in the rainfall-runoff model and local data in the disaggregation model.

countries in the region are available from Hughes (1997) where the daily VTI model (Hughes and Sami, 1994) was applied. These results suggest that a very wide range of NSE values are obtained, with the best being within the range of 0.4 and 0.7 in relatively humid catchments, but generally less than 0.5 in more arid areas. Typical NSE{ln} values were somewhat higher for humid areas (0.5–0.9), but much lower for arid areas (rarely greater than 0.2). The results shown in Fig. 3a and b (the Calibration-Local bars) suggest that many of the results for the disaggregation approach using observed volumes and local rainfall data fall into this range, but rarely reach the higher NSE values reported for some catchments in Hughes (1997). Fig. 4a illustrates that when ARC2 daily rainfall data are used, the calibrations are much poorer. An encouraging result is that the shapes of the observed FDCs are well reproduced by the disaggregation method (Figs. 3c,d and 4b).

The results for K7H001 demonstrate a potential problem with calibrating only using time series comparison statistics without examining the general shape of the simulated hydrographs relative to the observed. Table 4 indicates that the calibrated K and P_{Thresh} parameters are quite different to the other Southern Cape sites, and a closer examination of the time series indicates a relatively consistent 1 day shift in the observed, relative to the simulated runoff events. The reason for this is difficult to determine, but if the observed flow data are shifted backwards by 1 day, the best K and P_{Thresh} values change to 0.96 and 5.0 mm, respectively, while the NSE statistic improves to 0.562 from 0.333. The improvement is evident in better simulations of peak flows and recessions. Improvements were also obtained for the calibration based on ARC2 data. Miss-alignments of daily rainfalls and runoff responses are also evident in the time series of the other sites. However, they are not as consistent as is evident with K7H001 and do not appear to have had the same negative impact on the calibrated API parameters.

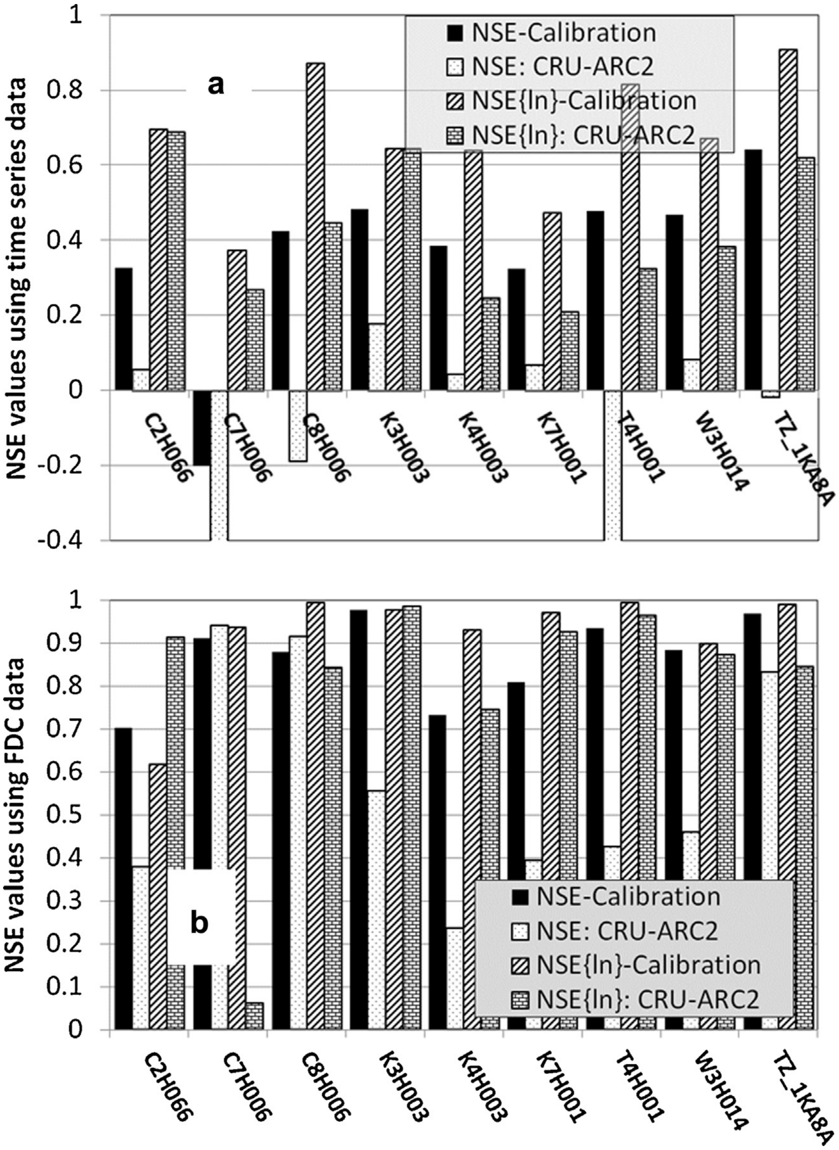

Fig. 4. NSE and NSE{ln} objective functions for daily time series (a) and FDCs (b) when the disaggregation model is based on ARC2 satellite data for the period October 2000 to September 2012. The terms used in the keys are similar to Fig. 3.

4.5. Simulated daily stream flow comparisons

Apart from the calibrations, Figs. 3 and 4 also present the results for three sets of simulations: (1) monthly volumes simulated with local rainfall data and disaggregated with the daily version of the same data (Local–Local); (2) monthly volumes simulated with CRU rainfall data and disaggregated with the local daily rainfall data (CRU–Local); (3) monthly volumes simulated with CRU rainfall data and disaggregated with the ARC2 daily rainfall data (CRU–ARC2). Inevitably, poor to bad monthly simulations (Table 3) cannot result in good daily simulations, regardless of the daily rainfall data used in the disaggregation (e.g. C2H006, C7H003, C8H005, K3H003, and W3H014). However, even many of

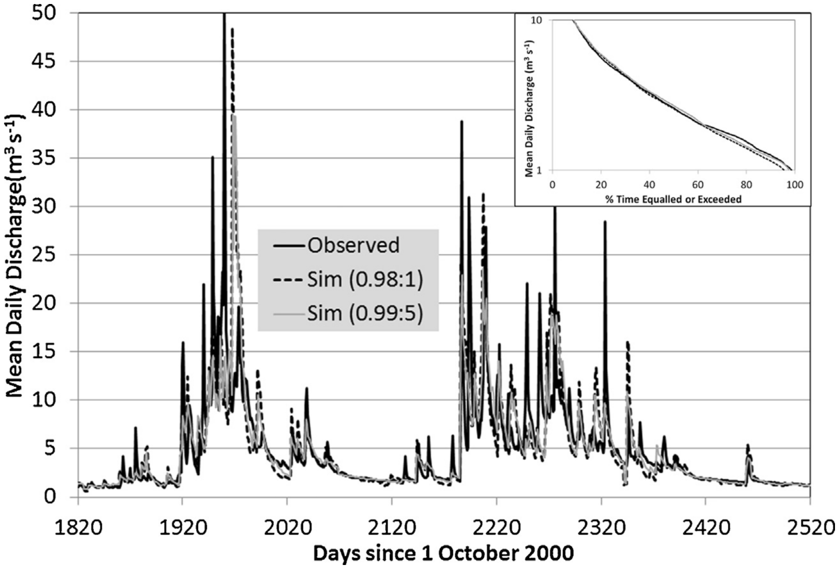

Fig. 5. Illustration of the sensitivity of the API parameters using two years of the simulated daily flows (Local–Local) for T4H001 (the values in the key refer to K: P_{Thresh}). The inset shows the main part of the observed and simulated FDCs.

these sites produce quite acceptable simulated daily FDCs (Figs. 3c,d and 4b) and the NSE{ln} statistics (Figs. 3b and 4a) indicate that the low flow regimes are generally better simulated than the higher flows. A detailed examination of the graphical results (monthly and daily), suggests that inadequate rainfall data are likely to represent one of the main problems. There are periods in all of the simulations where relatively high rainfalls do not correspond with increases in observed stream flow response, and vice versa. Even within a generally well simulated period (Fig. 5), there are some miss-matches between rainfall variations and flow responses that have a large impact on the NSE statistics. It is possible that some of these are related to spatially variable rainfalls that are not represented by the catchment averaged rainfall data, a problem that might be resolved by using smaller sub-basins in a semi-distributed model (i.e. modifying the model structure). However, this would also rely on having enough rain gauges to capture the spatial variability. This issue has not been explored in detail in this study, but there are certainly periods in some catchments where the available rainfall data are clearly not sufficiently representative and no hydrological model is able to generate a simulated runoff response in the absence of a simultaneous input rainfall signal. There will, of course, be other parts of the simulations where inadequacies in the model(s) structures and parameters, relative to real-world processes could lead to imperfect simulations of stream flow, even in response to accurate and representative climate inputs. Fig. 5 also illustrates that when both the monthly flow simulations and the daily rainfall data are representative, the disaggregation model is not very sensitive to moderate changes in the K and P_{Thresh} parameters.

Overall, there are not substantial differences between using the local and CRU rainfall data to force the monthly model. However, when the CRU monthly simulations are disaggregated with the ARC2 data, the results are substantially worse for all statistics (Fig. 4a and b). A large part of this problem is related to the generally poorer monthly simulations in the post-2000 period, and this could be a reflection of the declining rainfall data networks in recent decades that will inevitably affect the regional CRU data. However, the disaggregation calibration results using ARC2 data and observed volumes (Fig. 4) are also generally worse than when local rainfall data are used (Fig. 3). A further comparison was made using the monthly simulations based on local rainfall data disaggregated with ARC2 daily rainfalls. Overall, the results were very similar to those presented in Fig. 4, suggesting that the local monthly rainfall data for this period are no better than the CRU data.

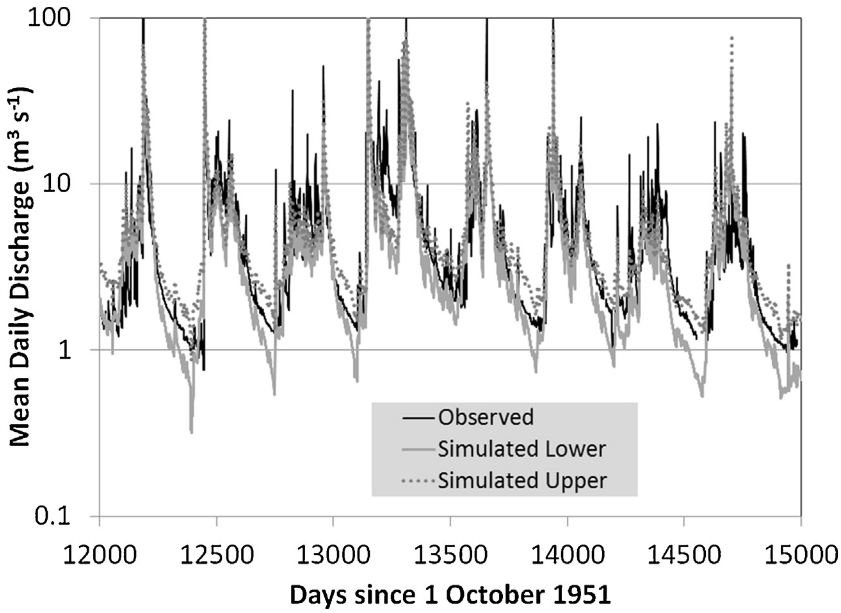

Fig. 6. 8 years of the observed time series for T4H001 together with the uncertainty bounds of disaggregated flows using 1917 monthly simulated flow ensembles and local rainfall data.

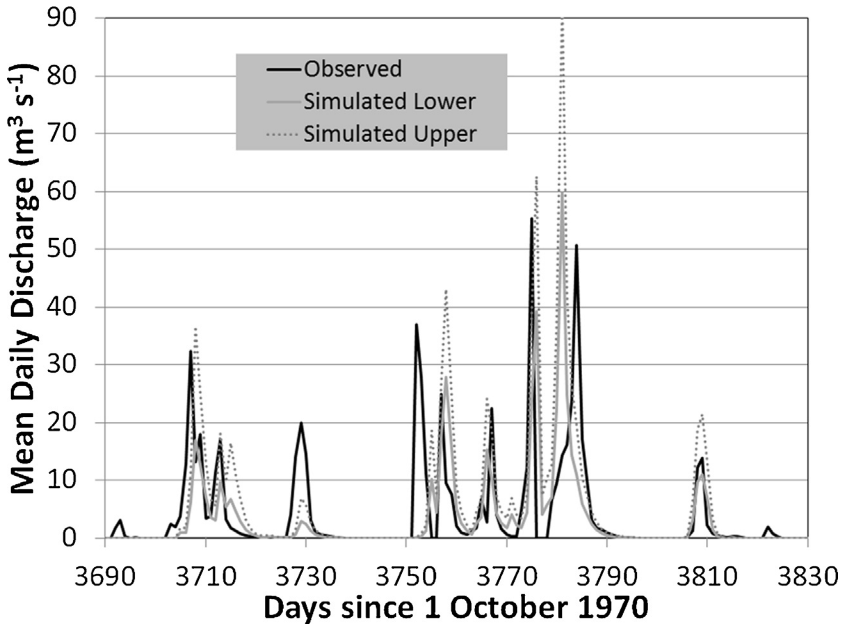

Fig. 7. 1 year of the observed time series for Bot_Tati together with the uncertainty bounds of disaggregated flows using 1540 monthly simulated flow ensembles and local rainfall data.

Fig. 6 presents an example (T4H001) of the use of ensembles of monthly simulated flow that are all disaggregated with the same local daily rainfall data. A total of 1917 ensembles were selected to be behavioural for this catchment on the basis of the NSE and bias statistics. Fig. 6 illustrates that the range of disaggregated ensembles follow the general seasonal and inter-annual variations of the observed data. The observed data only fall within the simulated range for 46% of the time. However, the situation is not much better for the monthly simulations (50% of observed bracketed by the behavioural simulations). The results for other humid and sub-humid sites where the monthly simulations are at least adequate (according to the criteria given in Section 3.3) are similar. However, the length of time that the observed data are bracketed by the range of disaggregated monthly ensembles for the semi-arid sites tends to be much less (14% for the BOT-Tati site, for example; Fig. 7). This is largely because the majority of the non-zero flows in the semi-arid sites are associated with almost immediate responses to rainfall that are highly affected by miss-matches between the timing of the daily rainfall and observed flow data (Fig. 7). For the more humid, catchments, the low flows are generally adequately simulated, even if many of the events are not properly time-matched.

5. Discussion and conclusions

There are two main components to this section. The first discusses whether the disaggregation approach can be used in data-scarce or totally ungauged situations and therefore, whether there is some potential for using global rainfall data, together with regionalised values for the parameters of the disaggregation method. The question of whether the Pitman model parameters can be satisfactorily regionalised is important, but beyond the scope of this paper (Hughes, 2013). The second question is whether the daily disaggregation results can be considered suitable for several (possibly inter-linked) purposes and whether there are any key limitations to the approach that can be identified. While the authors accept that there are certainly alternative approaches to generating daily time series of stream flow, it was not the purpose of this paper to compare different methods. The disaggregation method used has been designed to be a pragmatic approach to adding value to existing set-ups of monthly hydrological and water resources systems models. Notwithstanding the more restricted objectives of this study, it would certainly be useful in the future to compare the results of this simple disaggregation approach with the application of daily hydrological models coupled to rainfall disaggregation methods such as those described by Thober et al. (2014).

The FDC scaling columns of Table 4 do not provide a great deal of support for the possibility of regionalising the scaling parameters based on climate or physical catchment properties likely to affect the relationship between monthly and daily FDCs. This is partly because similar results can be obtained with different combinations of the three parameters and the fact that the high flow end of the FDC scaling is considerably affected by the length of the record and therefore the lowest % point value in the monthly data. The results for the group of catchments used in this study suggest that some general rules could be established for critical points in the relationship that might be useful in establishing appropriate parameters under ungauged situations. These include the point at which the two curves cross (generally a lower % point for arid and steep catchments), the ratio of peak daily to monthly flow (higher for arid and steep catchments), the duration of zero flows in arid catchments (from 10% to 20% greater for daily FDCs compared to monthly) and the ratio of monthly to daily low flows in more humid catchments (typically very low in strongly seasonal regimes, but higher in others). These rather qualitative observations need to be further quantified by comparing monthly and daily FDCs for more catchments in the region.

The API parameters also show a relatively high degree of scatter throughout the catchments with very few patterns emerging, except for a general trend of lower K parameters (steeper recessions) in semi-arid and steep catchments, as would be expected. There are no obvious patterns in the P_{Thresh} parameter variations. The problem with site K7H001 referred to in Section 4.4 illustrates the potential impact that data errors (or lack of temporal agreement between rain and flow events) have on the calibration of the API parameters, especially when only objective functions are relied on. It is also worth noting that the final daily flow simulations are not very sensitive to the API parameters as long as they remain within 'sensible' ranges (i.e. 0.96–0.99 for K and mostly 1.0–10.0 for P_{Thresh}: Fig. 5). It is therefore highly unlikely that using different API parameters for different periods (e.g. wet and dry) will make any substantial difference to the model results. For the same reason, split sample calibration-verification tests were not considered to be likely to add any value to the model assessments and were not undertaken as part of this study.

Apart from the regionalisation of the disaggregation parameters, the other issue is whether the globally available rainfall datasets are appropriate for simulating monthly and daily catchment stream flow responses. Table 3 compares the monthly simulation results using local and CRU rainfall data and in general terms there are few differences. There are some catchments where the CRU data perform much worse (K4H003, K7H001 and T4H001), some where the CRU results are better in some respects (C7H003, ZIM_B15 and ZIM_B29) and others where there is little to choose between the two results. It has been difficult to assess the real value of the ARC2 daily rainfall data, partly because there are many catchments without daily observed flows in the post-2000 years and partly because the monthly simulations for the other catchments are generally much poorer in this period. If the disaggregation model calibration (using observed flow volumes) results shown in Fig. 3 (using local rainfall data) are compared with those in Fig. 4 (using ARC2 rainfall data), it can be concluded that the ARC2 data are not as appropriate for use as local data. However, there are some catchments (C8H006 and T4H001) where the ARC2 calibrations are better and this may be an indication of very poor local rainfall data in these areas.

Four purposes have been identified as potentially benefiting from the disaggregation of simulated monthly flows to daily flows. The first is high flow analysis which includes flood frequency analysis, but could also include floodplain or wetland inundation studies. The second and third are water quality modelling and environmental flow assessments, where high flow simulations may also be important. The fourth is the scheduling of run-of-river abstractions, which may also be linked to environmental flow assessments.

Although no specific statistical tests for the ability of the model to simulate extreme events were undertaken, the results suggest that the reliability of the simulated high flows is generally inadequate for studies involving the analysis of flood magnitude and frequency. While there are some sites where the magnitude and frequency of high flow events are reasonably well represented by the model, this is not the case for most sites, where the very high observed flows are generally under-simulated. It is possible to improve the high flow simulations through re-calibration to a certain extent, but this often occurs at the expense of other parts of the simulations. It should be noted that these comments refer to the very extremes of the daily FDCs, while the remainder of the curves are generally well simulated (Figs. 3c,d and 4b).

The requirements for the second and third purposes are relatively similar and include accurate representation of FDCs, seasonality and event frequency, inter-annual variations and the details of the low flow regimes, including the duration of zero flows in semi-arid and arid catchments. For the majority of sites these aspects of the observed flow regimes are well represented in the simulations (see the comparison statistics presented in Figs. 3c,d and 4b that are based on FDC data). Further evidence of fitness for purpose lies in the fact that baseflow separations of observed and simulated daily flows yield similar baseflow percentages. This suggests that the modelling approach successfully simulates the balance between low-amplitude, high-frequency runoff responses and the higher-amplitude, low-frequency events, which is important for both purposes. These two stream flow responses could have substantially different water quality (salt and nutrient) signatures, and simulating the correct balance is therefore important. While accurate representation of high flows could also form part of the requirements for water quality and environmental flow studies, the focus is more likely to be on a wider range of events than for flood frequency analysis (e.g. from 10% exceedance and less) and these are generally better represented than individual major flood events. Inevitably, these conclusions are dependent upon the success of the monthly modelling and there are some sites (C7H003, W3H014 and ZAM_4005) where the combined simulations would certainly not be fit for purpose.

The final purpose referred to above is run-of-river abstraction scheduling, within which the simulation of the low flow regimes are likely to be of critical importance. The relatively high values for the transformed NSE statistic and the high objective function values for the FDC comparisons suggest that most of the simulations are fit for this purpose. Poor values are noted for C7H006 and the two Botswana (Tati and Ntse) sites, but run-of-river abstraction would not be considered a realistic option for these arid, ephemeral rivers.

The overall conclusion about the combined modelling approach is that, as with any other model, the quality of the results is very dependent upon the quality of the input rainfall data. However, for most of the sites included in the study, the simulations can be considered to be useful at least for the purposes of water quality modelling. While the CRU and ARC2 data have their limitations (particularly associated with spatial scale), the same is true of the local rainfall data that are available. There are very few catchments in southern Africa where there are sufficient rainfall stations to represent the typically high degree of spatial variability in input rainfall. Generalisations about the quality of the available rainfall data are difficult to make and clearly all hydrological studies should begin with a thorough examination of all available data sources, an issue that can easily be neglected in practical studies in data scarce areas, where any data that can be obtained are considered better than nothing. However, even thorough data checks can be inconclusive in data scarce areas where there may be no high confidence information against which to check the model input data. The results for the combination of CRU and ARC2 data for some of the sites are relatively encouraging, particularly in terms of reproducing the FDCs and seasonality. This is an important result given the increasing number of catchments in southern Africa for which there are no recent local rainfall data. The statistics presented in Fig. 4a are often a reflection of quite bad correspondence between daily changes in rainfall and flow. While this affects the ability of the model to accurately simulate sequences of daily flow, it does not mean that the results cannot be used for some purposes, where reproduction of the frequency characteristics of daily flows is the most important criterion for success.

The disaggregation approach therefore represents a parsimonious method of simulating daily time series from existing monthly simulations (with or without uncertainty), of which many already exist within a number of southern African countries. An obvious, but nonetheless important, conclusion is that the daily simulations will never be better than the monthly simulations, which are highly prone to inadequate climate data inputs. The monthly simulations may be considered adequate for their original purpose of yield estimation and water allocations, but there could be situations where the performance of the monthly model is too poor to support the daily disaggregation process. In these situations the results of the disaggregation approach may suggest that an existing monthly model setup and calibration should be re-visited. Poor monthly modelling results are more likely to occur in semi-arid catchments, which are known to be difficult to model at any time scale because of high spatial variability in both meteorological and runoff response conditions. Such problems are unlikely to be resolved through re-calibration without additional input data. Whether existing simulations, based on the limited availability of historical local climate data, can be successfully extended using CRU data and then disaggregated using ARC2 (or similar satellite derived products) data, remains open to question and this study has not been able to provide a definitive answer. The results derived from this study indicate that this success will be regionally variable, partly reflecting the spatial variability in the appropriateness of these global data sets, an issue that is not unique to this study (Xie and Arkin, 1995; Hughes, 2006; Voisin et al., 2008; Prakash et al., 2014).

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